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Keywords: Running; Dynamic stability; Nonlinear dynamics; Variability; Motor control.

Word count: 3267 words

18 Abstract

19 Research has indicated that human walking is more unstable in the secondary, rather than primary plane
20 of progression. However, the mechanisms of controlling dynamic stability in different planes of
21 progression during running remain unknown. The aim of this study was to compare variability (standard
22 deviation and coefficient of variation) and dynamic stability (sample entropy and local divergence
23 exponent) in anterior-posterior and medio-lateral directions in forward and lateral running patterns. For
24 this purpose, fifteen healthy, male participants ran in a forward and lateral direction on a treadmill at their
25 preferred running speeds. Coordinate data of passive reflective markers attached to body segments were
26 recorded using a motion capture system. Results indicated that: 1) there is lower dynamic stability in the
27 primary plane of progression during both forward and lateral running suggesting that, unlike walking,
28 greater control might be required to regulate dynamic stability in the primary plane of progression during
29 running, 2) as in walking, the control of stability in anterior-posterior and medio-lateral directions of
30 running is dependent on the direction of progression, and 3), quantifying magnitude of variability might
31 not be sufficient to understand control mechanisms in human movement and directly measuring dynamic
32 stability could be an appropriate alternative.

33

34 1. Introduction

35 Studies on walking have indicated that humans are more unstable in the medio-lateral (ML; i.e. frontal
36 plane, secondary plane of progression) compared to anterior-posterior direction (AP; i.e. sagittal plane,
37 primary plane of progression; Bauby & Kuo, 2000; Donelan et al., 2004; Kuo, 1999). The implication is
38 that there might be greater neuromuscular control of ML direction fluctuations through sensory feedback
39 originating from visual, vestibular and proprioceptive systems (Bauby & Kuo, 2000; Wurdeman et al.,
40 2012). A study on lateral stepping gait has also supported the findings that there is greater control in the
41 secondary plane of progression suggesting that control of motion depends on the direction of progression
42 (Wurdeman et al. 2012). These studies, however, have all concentrated on human walking and little is
43 known about the mechanisms of maintaining stability in the AP and ML directions in running gait.
44 Maintaining stability in running is an important factor required to preserve balance, prevent falling and
45 enhance performance in dynamic environments such as sport, e.g., agility (Mehdizadeh et al., 2014).
46 Since running mechanics are different to walking (Cappellini et al., 2006; Dugan & Bhat, 2005;
47 Novacheck, 1998; Sasaki & Neptune, 2006), distinct control strategies might be required to maintain
48 stability in different planes of progression in running.

49 However, how to characterize the control mechanisms in maintaining stability has been the subject of
50 many studies in human movement science. Examination of movement variability has been suggested as
51 an appropriate method to understand mechanisms of motion control (Collins & Kuo, 2013). Nonetheless,
52 there is an ambiguity surrounding the appropriate method of quantifying variability. While earlier studies
53 tended to focus on the *magnitude* of variability (Bauby & Kuo, 2000; Donelan et al., 2004), in a recent
54 study by Wurdeman et al. (2012), adoption of standard deviation (SD) and coefficient of variation (i.e.,
55 SD divided by mean; CoV), as the measures of magnitude of variability, resulted in contradictory findings.
56 That is, while SD was greater in the primary plane of progression, the result for CoV was the opposite.
57 This was argued to be mainly due to significantly different scales of step length and step width.
58 Nevertheless, this outcome led to some confusion in the literature.

59 An alternative approach to clarify this source of confusion could be to quantify the *structure* of movement
60 system variability (i.e. dynamic stability), instead of simply measuring the magnitude of variability. The
61 implication is that, if dynamic stability is lower in a specific direction, higher control might be required in
62 that direction. In a study by Wurdeman and Stergiou (2013), it was shown that largest Lyapunov
63 exponent (LyE), as a measure of dynamic stability, was greater in the ML direction. This was indicative
64 of lower local dynamic stability in the ML direction, thus requiring increased control. Using LyE to
65 quantify dynamic stability, McAndrew et al. (2010; 2011) demonstrated that there is greater sensitivity of
66 body movements to perturbations in the ML direction during walking, supporting the view that there is a
67 lower level of dynamic stability in the ML direction. Furthermore, using the nonlinear measure of sample
68 entropy (SaEn), Lamothe et al. (2010), showed that increased regularity of kinematic time series is
69 associated with higher stability, and more control in human locomotion. Taken together, the data from
70 these studies suggested that using nonlinear measures to quantify dynamic stability may be an appropriate
71 method to characterize control mechanisms in human locomotion.

72 In studies of planar running robots, it has been shown that passive running robots are marginally stable,
73 thus requiring control input signals to accelerate recovery from perturbations (Hyon & Emura, 2004;
74 Raibert et al., 1989; McGeer, 1990). These results signify that, in human running, the control of dynamic
75 stability might require additional control signals in the direction of progression to prevent perturbations
76 from hindering displacement.

77 The aims of this study were, therefore, to compare variability and dynamic stability in both the AP and
78 ML directions and to determine whether they differed in forward and lateral running patterns. Variability
79 was quantified using linear measures of standard deviation and coefficient of variation. In addition,
80 nonlinear measures of sample entropy and the local divergence exponent were adopted to quantify
81 dynamic stability. It was hypothesized that lower levels of dynamic stability might be observed in the
82 primary plane of progression in both forward and lateral running. Furthermore, it was hypothesized that,
83 as in walking, control of dynamic stability in running depends on the direction of progression.

84 2. Methods

85 2.1. Participants

86 15 healthy male participants were investigated in this study. Their average age was 24.1 ± 1.0 years with
87 average mass and height of 68.8 ± 3.8 kg and 1.76 ± 0.04 m, respectively. None of the participants suffered
88 from any musculoskeletal injuries at the time of the experiment. All participants provided written
89 informed consent before participation in the study. The ethics committee of Amirkabir University of
90 Technology approved the experimental procedure.

91 2.2. Marker placement

92 Seventeen passive reflective markers (14 mm diameter) were attached to the skin of each participant at
93 the right and left bony landmark on the second metatarsal head (toe), calcaneus (heel), lateral malleolus
94 (ankle), mid-tibia, lateral epicondyle of knee (knee), mid thigh, anterior superior iliac spine and also on the
95 sacrum, midway between posterior superior iliac spines, 10th thoracic vertebrae (T10) and 7th cervical
96 vertebrae (C7). For the purpose of this study, only foot and C7 markers were used for further analyses.

97 2.3. Task

98 Before starting the experiment, participants were given time to familiarize themselves with running in a
99 forward, and also in their own lateral direction, on the treadmill. During the actual tests, all participants
100 ran on a motorized treadmill (Cosmed[®] T150, Rome, Italy) at their preferred running speeds (PRS). PRS
101 in each direction was recorded following approaches similar to protocols described in previous works by
102 Dingwell and Marin (2006), Jordan et al. (2009) and Jordan et al.(2007). Each participant was asked to
103 run for 2 minutes in each direction. In lateral running, all participants ran to their right side of the body
104 while looking forward. They were not allowed to cross their feet in lateral running. Sufficient rest periods
105 were allocated between the tests to allow participants to recover. All participants wore their own
106 comfortable running shoes.

107 *2.4. Data recording*

108 The three-dimensional coordinate data of the markers were recorded using five Vicon[®] VCAM motion
109 capture calibrated cameras (Oxford Metrics, Oxford, UK) at the sampling frequency of 100
110 samples/second. Reconstruction and labelling were performed using Vicon[®] Workstation software
111 (Oxford Metrics, Oxford, UK).

112 *2.5. Data analysis*

113 *2.5.1. Linear measures of foot placement variability*

114 For both running patterns, the variability was quantified for the foot placement variables introduced in
115 Table 1. To calculate the linear measures of foot placement variability, position data were first filtered
116 using a fourth-order low-pass Butterworth filter with 10 Hz cutoff frequency. Position data for individual
117 strides were time-normalized to 100 data points for all participants. For forward running, each stride cycle
118 was determined from point of heel contact to heel contact of the same foot. Heel contacts were identified
119 as the minima in the ankle vertical time series (Li et al., 1999). For lateral running, however, since
120 participants ran on their forefoot and had toe strikes instead of heel strikes, this algorithm was operated
121 using toe markers. Foot center of mass (COM) was determined as the midpoint of the heel and toe
122 markers during foot contact with the treadmill surface (Wurdeman et al., 2012). The calculation of
123 variables was based on the work of Balasubramanian et al. (2010) and Wurdeman et al. (2012) and
124 modified for analysis of running patterns. For forward running, the introduced variables were calculated
125 for both right and left legs. However, due to the similarity of the results, we report the results of right leg
126 here. For lateral running however, the foot placement variables were calculated and reported for both lead
127 and lag legs. The standard deviation (SD) of foot placement variables and coefficient of variation (i.e. SD
128 divided by the mean; CoV) were calculated over 100 strides as the linear measures of foot placement
129 variability.

130

131

132 *2.5.2. Nonlinear measure of dynamic stability*

133 Sample entropy (SaEn) and the Local divergence exponent (LDE) were calculated as nonlinear measures
134 of dynamic stability. Details on the calculation of SaEn and LDE already exist in the literature (Bruijn et
135 al., 2013; Bruijn et al., 2009; Dingwell & Marin, 2006; Lamothe et al., 2010; Yentes et al., 2013).

136 SaEn quantifies the degree of predictability or regularity of a time series (Lamothe et al., 2010), and is
137 defined as the probability that a sequence of data points, having repeated itself within a tolerance r for a
138 window length m , will also repeat itself for $m+1$ points, without allowing self-matches (Lamothe et al.,
139 2009). Smaller SaEn value indicates greater regularity and predictability of the time series. Greater
140 regularity of the kinematic time series in human movement has been reported as an indication of higher
141 stability and more control (Lamothe et al., 2010). To calculate SaEn, two input parameters m , the window
142 length that will be compared, and r , the similarity criterion, are needed. To determine these parameters,
143 the approach suggested by Yentes et al. (2013) was applied in the present study. That is, a range of m
144 ($m=2$ and $m=3$) and r ($r=0.1$ and $r=0.2$ times the standard deviation of the time series) were used.
145 However, since the results were consistent between all combinations of m and r , $m=2$ and $r=0.2$ were
146 used in this study. SaEn was calculated based on the foot placement variables introduced in Table 1.

147 The LDE measures the exponential rate of divergence of neighbouring trajectories in the state space
148 (Rosenstein et al., 1993). Since LDE measures the rate of divergence of the trajectories, a greater LDE
149 value is indicative of lower levels of local dynamic stability of a system. To calculate the LDE first, a
150 state space with appropriate dimension and time delay was reconstructed based on Takens's (1981) theory
151 (Kantz & Schreiber, 2004; Takens, 1981). Time delay is determined as the first local minimum of average
152 mutual information (AMI) function (Fraser, 1986). A time delay of 10 samples was found to be
153 appropriate for data associated with the AP and ML directions. In addition, a Global False Nearest
154 Neighbors (GFNN) measure was used to determine embedding dimension (Kennel, et al., 1992). For the

155 purpose of this study, an embedding dimension of 5 was calculated for data associated with AP and ML
156 directions. All time series were time-normalized to an equal length of 10000 points. A total number of
157 100 consecutive strides were analyzed. The approach implemented in this study was introduced by
158 Rosenstein et al. (1993), which is most suitable for a finite time series. The LDE was determined from the
159 slopes of a linear fit in the divergence diagrams in the range of 0 to 0.5 stride (approximately 0 to 50
160 samples) (Bruijn et al., 2009). In the present study, all LDE values were presented as the rate of
161 divergence/stride. Since the priority of the motor control system is maintaining stability of the upper body
162 (Kang, & Dingwell, 2009), we quantified the LDE of trunk (C7 marker) motion (Dingwell & Marin,
163 2006).

164 Due to possible loss of information at critical points, non-filtered time-series were used to calculate both
165 LDE and SaEn (Dingwell & Marin, 2006). For SaEn, the time series were also normalized to unit
166 variance which results in the outcome being scale-independent (Lamothe et al., 2010). In addition, due to
167 the nonstationarities encountered in the biological time series, differenced time series were used to
168 calculate the LDE and SaEn (Yentes et al., 2013).

169 *Statistical analyses*

170 Data associated with forward and lateral running were analyzed separately. Separate two-way repeated
171 measure analyses of variance (ANOVA) were performed to determine the effect of plane of progression
172 (AP or ML) and gait event (foot contact and foot off) on SD, CoV and SaEn. In addition, separate
173 independent t-test analyses were performed to determine the difference in the LDE between AP and ML
174 directions. Statistical significance was set at $P < 0.05$.

175 3. Results

176 3.1. Standard deviation (SD)

177 The results of ANOVAs for SD values are presented in Table 2 and Figure 1. For forward running, only
178 the plane factor displayed a statistically significant effect on SD ($F=54.72$, $P < 0.001$), with the AP

179 direction exhibiting higher SD values (Figure 1, top left). For lateral running, the results indicated that
180 interaction effects were statistically significant for the lead leg ($F= 8.40$, $P=0.01$). Simple main effect
181 analyses revealed that SD was significantly greater in the ML direction at foot contact (Figure 1, down
182 left; $P<0.05$). For lag leg, however, only the plane factor significantly affected SD values ($F= 9.66$,
183 $P=0.009$), with the ML direction exhibiting higher SDs (Figure 1, down left).

184 *3.2. Coefficient of variation (CoV)*

185 The results of ANOVAs for CoV are presented in Table 3 and Figure 1. For forward running, only the
186 plane factor displayed a statistically significant effect on CoV ($F=25.46$, $P<0.001$), with ML direction
187 exhibiting higher CoV values (Figure 1, top right). For lateral running, the results also indicated that
188 interaction effects were statistically significant for both lead ($F= 29.07$, $P<0.001$) and lag legs ($F= 27.93$,
189 $P<0.001$). The results of simple effects analyses revealed that while for the lead leg, AP direction had
190 significantly greater CoV at foot contact, for the lag leg, this was the case at foot off (Figure 1, down
191 right; $P<0.05$).

192 *3.3. Sample entropy (SaEn)*

193 According to the results presented in Table 4 and Figure 2, for forward running, only the interaction effect
194 was statistically significant for SaEn ($P=0.02$). Simple effects analyses revealed that the value of SaEn
195 was greater in the AP direction at heel strike ($P<0.05$). For lateral running, there was a significant
196 interaction effect for the lead leg ($F=7.35$, $P=0.01$). Simple effects analyses indicated that SaEn was
197 significantly higher in the ML direction at foot contact ($P<0.05$). For the lag leg on the other hand, no
198 significant effects of plane, gait event, or their interactions were found ($P>0.05$).

199 *3.4. Local divergence exponent (LDE)*

200 The results of LDE for C7 marker are shown in Figure 3. For forward running, the value of LDE was
201 significantly higher in the AP direction ($P<0.001$), indicative of lower local dynamic stability in the AP

202 direction. For lateral running, the results showed that the LDE was significantly higher in the ML
203 direction ($P<0.001$).

204

205 4. Discussion

206 This study sought to compare variability, as well as dynamic stability, in running patterns in AP and ML
207 directions. The results appeared to confirm the initial hypotheses. That is, there was evidence of lower
208 dynamic stability in the primary plane of progression in both forward and lateral running. Results implied
209 that greater control might be required to maintain dynamic stability in the primary plane of progression in
210 running gait.

211 *4.1. Linear measures of variability*

212 The results of our study revealed that measurement of foot placement variability using linear methods
213 (SD and CoV) led to some contradictory outcomes. That is, while the results of SD analyses showed that
214 foot placement variability was greater in the primary plane of progression (Table 2 and Figure 1), the
215 results of CoV measures indicated that foot placement variability was higher in the secondary plane of
216 progression (Table 3 and Figure 1). Similar cases were encountered in the study of Wurdeman et al.
217 (2012) on walking. They reported that this outcome might be primarily due to the significantly different
218 scales of step length and step width in running. Arellano and Kram (2011) reported that there is minimal
219 variability of step width in forward running, suggesting that there might be little need for active control in
220 the ML direction. However, greater magnitude of variability could also be interpreted as the result of poor
221 system control. In other words, higher magnitude of variability could signify that it might be unnecessary
222 for a system to control movement in that direction (see the study of Rosenblatt et al., 2014 on walking).
223 Therefore, it could be argued that measuring magnitude of variability might not be an appropriate
224 approach to understand control mechanisms in human locomotion.

225 4.2. *Dynamic stability in primary versus secondary planes of progression*

226 Our results on quantifying dynamic stability using both SaEn and LDE suggest that there are lower levels
227 of dynamic stability in the primary plane of progression in running. That is, our observations of greater
228 values of SaEn in the primary plane of progression (Table 4 and Figure 2) demonstrate that the foot
229 placement time series were less regular in the primary plane of progression. Greater regularity of the
230 kinematic time series in human movement has been reported as an indication of higher stability and more
231 control (Lamoth et al., 2010). Therefore, our results on SaEn suggest that dynamic stability was lower in
232 the primary plane of progression which requires increased control to regulate dynamic stability. Our
233 findings also indicated that local dynamic stability was lower in the primary plane of progression in both
234 running patterns (Figure 3). The lower levels of dynamic stability in the primary plane of progression
235 could imply that more control might be required to maintain system dynamic stability in this direction.
236 Taken together, these results imply that, since nonlinear measures quantify dynamic stability of
237 locomotion directly, they might be more appropriate to investigate the mechanisms of control in human
238 locomotion.

239 Studies on designing running robots, has shown that active control input is required to facilitate any
240 recovery from perturbations (Hyon & Emura, 2004; McGeer, 1990; Raibert et al., 1989). These findings
241 are therefore, aligned with the results of our study where participants tried to functionally respond to
242 inherent local perturbations (for a study on the stability of running in the ML direction, see Seipel &
243 Holmes, 2005).

244 Furthermore, the lower dynamic stability in the primary plane of progression in both forward and lateral
245 running implies that, as in walking (Wurdeman et al., 2012), the control of stability in AP and ML
246 directions of running, is also dependent on the direction of progression, and is not set *a priori*, based on
247 anatomical planes of the human body.

248

249 *4.3. Differences between walking and running in controlling stability*

250 The findings of this study imply that the mechanisms of controlling stability differ between walking and
251 running. That is, while previous studies on walking have indicated that there is higher dynamic stability in
252 the primary plane of progression (Bauby & Kuo, 2000; Donelan et al., 2004), our data suggested that
253 dynamic stability is lower in the primary plane of progression in running. This distinction might be
254 caused by differences in the mechanics of walking and running. That is, since there is a flight phase in
255 running where both feet are off the ground, increased sensory feedback might be required to control foot
256 placement adaptation in the primary plane of progression.

257 *4.4. Limitations*

258 Calculation of SaEn is highly sensitive to the window length, m , and the similarity criterion, r . Therefore,
259 extensive effort should be assigned to the appropriate choice of m , and r . For the purpose of this study, the
260 results were consistent over all pairs of m , and r that we investigated in our study.

261 5. Conclusions

262 There are three main conclusions associated with this study. First, our findings indicated that there is
263 lower dynamic stability, in the primary plane of progression during both forward and lateral running.
264 These data suggested that, unlike walking, greater control might be required to regulate system stability in
265 the primary plane of progression during running. Second, results demonstrated that as in walking, control
266 of stability in AP and ML directions of running, is dependent on the direction of progression. Finally, our
267 data indicated that measuring the magnitude of movement variability might not be sufficient to
268 understand control mechanisms in human movement, and quantifying system dynamic stability could
269 serve as an appropriate alternative.

270 6. Acknowledgment

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272 performed at the Biomechanics Laboratory, University of Social Welfare and Rehabilitation Sciences.

273 **Conflict of Interest:**None

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275

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370 Tables:

371 Table 1: foot placement variables and their definitions. Pelvis center of mass (COM) was calculated as the
372 centroid of the three S1 and right and left anterior superior iliac spine markers in the horizontal plane. In
373 forward running, the variables were calculated for right leg. In lateral running, the variables were
374 calculated for both lead and lag legs.

Variable name	Definition
Forward running	
AP-HS	Distance in AP direction between foot COM and pelvis COM at heel strike
AP-TO	Distance in AP direction between foot COM and pelvis COM at toe off
ML-HS	Distance in ML direction between foot COM and pelvis COM at heel strike
ML-TO	Distance in ML direction between foot COM and pelvis COM at toe off
Lateral running	
AP-FC	Distance in AP direction between foot COM and pelvis COM at foot contact
AP-FO	Distance in AP direction between foot COM and pelvis COM at foot off
ML-FC	Distance in ML direction between foot COM and pelvis COM at foot contact
ML-FO	Distance in ML direction between foot COM and pelvis COM at foot off

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381 Table 2: results of two-way ANOVA test for standard deviation (SD) of foot placement in forward and
 382 lateral running.

	Plane			Gait event			Interaction		
	F	P-value	η^2	F	P-value	η^2	F	P-value	η^2
Forward	54.72	<0.001	0.82	4.64	0.05	0.27	0.05	0.82	0.004
Lateral Lead	10.79	0.007	0.47	4.17	0.06	0.25	8.40	0.01	0.41
Lateral lag	9.66	0.009	0.44	2.08	0.17	0.14	0.01	0.90	0.001

383 η^2 = effect size (partial eta-squared).

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387 Table 3: results of two-way ANOVA test for coefficient of variation (CoV) of foot placement in forward
388 and lateral running.

	Plane			Gait event			Interaction		
	F	P-value	η^2	F	P-value	η^2	F	P-value	η^2
Forward	25.46	<0.001	0.68	0.02	0.87	.002	2.24	0.16	0.15
Lateral Lead	8.71	0.01	0.42	20.82	0.001	0.63	29.07	<0.001	0.70
lag	41.59	<0.001	0.77	29.89	<0.001	0.71	27.93	<0.001	0.70

389 η^2 = effect size (partial eta-squared).

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394 Table 4: results of two-way ANOVA test for sample entropy (SaEn) of foot placement in forward and
 395 lateral running.

	Plane			Gait event			Interaction		
	F	P-value	η^2	F	P-value	η^2	F	P-value	η^2
Forward	3.48	0.08	0.18	2.11	0.16	0.12	6.35	0.02	0.29
Lateral Lead	4.54	0.05	0.23	0.27	0.60	0.01	7.35	0.01	0.32
Lateral lag	1.23	0.28	0.07	0.04	0.82	0.003	0.005	0.94	0.00

396 η^2 = effect size (partial eta-squared).

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401 Figure captions:

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403 Figure 1: results of standard deviation (SD) and coefficient of variation (CoV) for forward (top) and
404 lateral (down) running patterns. For lateral running, the results for lead and lag legs are shown in separate
405 columns. Error bar represent standard deviations.

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407 Figure 2: results of sample entropy (SaEn) for forward (top) and lateral (down) running patterns. For
408 lateral running, the results for lead and lag legs are shown in separate columns. Error bars represent
409 standard deviations.

410 Figure 3: results of local divergence exponent (LDE) calculated for C7 marker for forward and lateral
411 running patterns. Error bars represent standard deviations. Note that in forward running, AP is the primary
412 plane of progression whereas in lateral running, ML is the primary plane of progression.

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